Volumetric Image Visualization

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Task 4

1 Object segmentation

In this task, we will use convolution by random filters, rectified linear activation, and selection of the most suitable activation channels to compose an input multi-channel image for IFT-based image segmentation. Assuming an interactive process, you may quickly select channels and markers suitable for the segmentation of each image. Make your code general enough to evaluate it on any available 3D image. However, you should demonstrate the effectiveness of your solution using the available images in this folder for the glioblastoma problem.

For a given 3D grayscale image $\hat{I} = (D_I, I)$, spheric adjacency relation A with radius $r \geq 1$, and the desired number N of filters, generate a set $K = (A, W)$ of random filters in which the weight $w(q) \in W$ of each voxel $q \in A(p)$ adjacent to the origin $p \in D_I$ in A is randomly obtained in $[0, 1]$. Such weights should be subtracted by their mean value and stored in the filter bank, such that the mean weight of each filter is 0 (i.e., each filter is a local texture/border enhancement operator). The convolution between the image and the filter bank followed by ReLU activation will generate a multi-channel image $\hat{J} = (D_I, \vec{J})$ in which some channels J_k, $k \in [1, N]$, may be more suitable than others for object segmentation – i.e., they enhance object features important for segmentation. Visualize the channels and interactively select the ones that best enhance object features (interior/borders) related to the immediate background.

Figure 1 illustrates examples of activation channels suitable to compose desirable object features in brain tumor segmentation. Figure 1a shows a slice with a glioblastoma in a T1GD image, in which the mask of the enhanced tumor is shown in yellow and the mask of the necrotic core is shown in purple. Figures 1b-1c show examples of suitable activation channels for enhanced tumor and necrotic core segmentation, respectively. Similarly, Figure 1d shows a slice with the same glioblastoma in a FLAIR image, in which the edema is shown in orange. Figures 1e-1f show examples of suitable activation channels for edema segmentation.

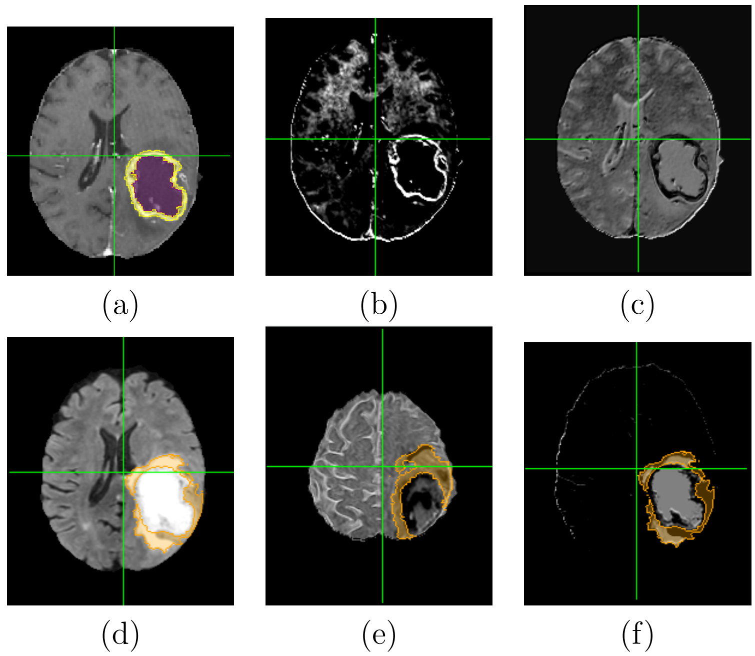

Figura 1: Glioblastoma segmentation. Slices of (a) T1GD and (d) FLAIR images, with suitable activation channels for (b) enhanced tumor, (c) necrotic core, and (e-f) edema.

You may also merge the selected channels from both T1GD and FLAIR images such that the resulting multi-channel image $\hat{J} = (D_I, \vec{J})$ can be explored to estimate arc weights for IFT-based image segmentation from user-drawn markers. You can use itksnap to visualize 3D images and select markers. The activation channels can also be normalized and saved as .nii.gz images for visualization. Examples of arc-weight functios are:

$$\begin{aligned} w(p,q) &= \|\vec{J}(q) - \vec{J}(p)\|, \\ w(p,q) &= \|\vec{J}(q) - \vec{\mu}(T_p)\|, \\ w(p,q) &= \|\vec{G}(q)\|, \\ w(p,q) &= J_{\max} - J_k(q), \end{aligned}$$

where $\vec{\mu}(T_p)$ is the mean feature vector of the optimum-path tree that contains p by the time it tries to conquer q (the dynamic tree formulation), $\vec{G}(q)$ is a gradient vector estimated at q (see formula in the slides of lecture 9), and J_k is one of the activation channels with $J_{\max}$ being its maximum value – e.g., the one in Figure 1f may allow the segmentation of the necrotic core from a single internal marker followed by a threshold on the optimum-path costs. You may explore the minimization of the cost map for the $f_{\max}$ path-cost function from internal and/or external markers. Devise different IFT-based algorithms for each object.